Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

Artificial Intelligence is Used in A Smart City to Understand the Emotional Pulse of its Residents

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Article Info
Page Number: 247-256
Publication Issue:
Vol. 69 No. 1 (2020)

Article History
Article Received:
12 September 2020
Revised: 16 October 2020
Accepted: 20 November 2020
Publication: 25 December 2020

Abstract
India, which is in the tropical wet and dry area, receives a huge amount of precipitation each year, with the monsoon season being the main contributor. The environment resulting challenges also has led to significant improvements in the average rain distribution and its volatility, as well as the severity and frequency of severe rainfalls. Rain also exhibits great temporal and geographic volatility. Different Time-series prognostication models for predicting rain, including Holt's Linear Trend methodology (HLTM), Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH), Holt's Winter Seasonal Methodology (HWSM), and seasonal Autoregressive Integrated Moving Average, were used in this study (SARIMA). In order to analyse the most basic time-series prognostication model, a comparison analysis was built. The HWSM model was determined to have the lowest error rate when compared to the other models. Mean square error (MSE), Root Mean square error (RMSE), and Mean Absolute Error are the analysis criteria used to compare different time-series rain forecast methods (MAE). The HWSM model exhibited, by far, the lowest error rate of the other models, with error rates of 4.767 and 4.343 RMSE, 1.51 and 1.432 MAE, and 25.65 and 24.75 MSE for datasets 1 and 2, respectively.

Introduction

Since rainfall data should be recorded over a period of time, it is considered a statistical analysis. In areas including business, ecological prognostication, and technological prognostication, statistical prognostication is employed as a decision-support tool. Due to connectivity, a variety of models and methodologies for statistical forecasting have been developed that enable various types of inputs, anticipated outcomes, and straightforward implementation. Our country's economy is based primarily on agriculture. The value of the harvest has changed more recently due to uncertain environmental condition patterns and other market changes. Despite this, farmers continue to ignore these hazards, which results in destroyed crops and significant losses. Because of this, they are unable to determine which harvest would result in higher revenues.

Lack of understanding about various agricultural pests and resulting yearly precipitation amounts causes farms to be destroyed. The economy of Asia still consists mostly of agriculture, which would be strongly correlated with the amount of precipitation received annually [1]. Geophysical and atmospheric science both depend on accurate precipitation forecasts. On the other side, current systems frequently provide low error rates and perform well in terms of prediction. Numerous situations call for poor performance from mathematical prediction models. The whole prediction performance and error rate for precipitation prediction were investigated throughout this examination, which examined and assessed a number of time-series foretelling models. A variety of techniques are used to estimate the annual precipitation, including Multi-Layer Perceptron (MLP), Deep Neural Networks (DNN), Random Call Forest (RDF), K-Nearest Neighbors (KNN), K-Suggests that clump (KMC), Support Vector Machine (SVM), Simulated Neural Network (SNN), Transfer learning (TL), automobile Encoder Neural Network (AENN), and Convolution Neural Network (CNN) [Such methods also incorporate the techniques from the metric capacity unit [3] and Deep Learning (DL) [4], both of which have application potential. The following might serve as a summary of the rest of this article: In Section Two, pertinent analysis is presented, in Section Three, the study's region is covered, and in Section Four, several approaches for the prediction model for precipitation estimation are presented, Section five contains the observations and outcomes, and Section vi concludes the analysis.

1. Related Works

Researchers, academicians, and specialists used a variety of techniques to predict the frequency of precipitation by taking into consideration monumental efficiency assessment metrics, specifically RMSE, variance (SD), Learning rate (LR), MAE, Accuracy, MSE, Mean Absolute proportion Error (MAPE), F1-Measure, Sensitivity, and Nash-Sutcliffe efficiency (NSE) (PET). An overview of precipitation prediction models is provided in Table 1.

.**Table 1.** Rainfall Prediction Models – A Survey.

Research	The approach employed to predict rainfall	Meteorological characteristics used	Rainfall prediction before based on Location and no. of days	Evaluation designs for measuring performance	Dataset	Experimental Survey	Limitations
A.B. Wicaksono Putra	CNN, SNN	Sunlight radiation, Pressure	Indonesia &Thirt	MSE, MAPE	Samarinda meteorological centers	MSE=0.00098 MAPE=0.00	Improve accuracy by using

et al., (2020). [5]		on sea level	y days		from 2006 to 2019	05	AENN & DNN models
A.R. Naik et al., (2020). [6]	SVM, decision tree, RDF	moisture, warmth, and Barometric Pressure	Global survey	Adam optimizer	It is a survey paper. They concluded that DNN predict rainfall predictions accurately		
M.M.R. Khan et al., (2020). [7]	Long Short Term Memory	Temperature and geopotential altitude	Bangladesh 7 days	Standard deviation and Mean error	Kaggle website [13] for 1901-2015	Mean = 0.38 Std Devi- 0.63	By accelerating processing, failure rate can be reduced
E.Hussein et al (2020). [8]	SVM	Sunlight radiation, pressure in sea, Breeze speed	USA & thirty days	MAE and RMSE	Kaggle website - American dataset	Mapping rainfall, forecasting weather with minimum errors	Globally extended
A Kumar et al., (2021). [9]	ML designs	Pressure in sea, cloud point	India & 7 days	Accuracy	Rainfall in summer from 1991-2019	Accuracy=89.98%	More parameters included for research
Y.R.Sari et al., (2020). [10]	CNN & 1 day	Temperature, breeze speed and cloud	Indonesia & 2 weeks	Accuracy, missing	Dataset from reference [14]	Accuracy=81.46% & miss = 0.0018.	Suggestions for improving CNN
S. Haribabu et al., (2021). [11]	SVM, MLP, KMC	wetness, warm	Not specified	Accuracy	Data from reference [12]	High precision levels generated	Efficiency can be improved for other factors.

2. Case Study Location

Telangana, India's 29th state, was established on June 2, 2014, following the detachment from Andhra Pradesam (AP), situated in south India. AP surmised geographic directions of

15°55' N and 19°55' N scope and 77°10' E to 81°50' E longitude, and has limits with AP. The long stretch of Telangana state's South West Rainstorm (SWM) precipitation in August (31.35%), sought after by 19.6%, 30.6%, 18.4 percent for June, July, and September months. The state encounters annual rainfall of 78.65% only from SWM season.

Fig.1 portrays the regions of Telangana in India. Fig.2 portrays state's divisions. Territories in Telangana's north-east regions considered the most water compared with the territory's of south during June to September in SWM season.

Table2 displays the greatest storm over the most recent thirty years (1989-2018) for each SWM seasons in Telangana state.

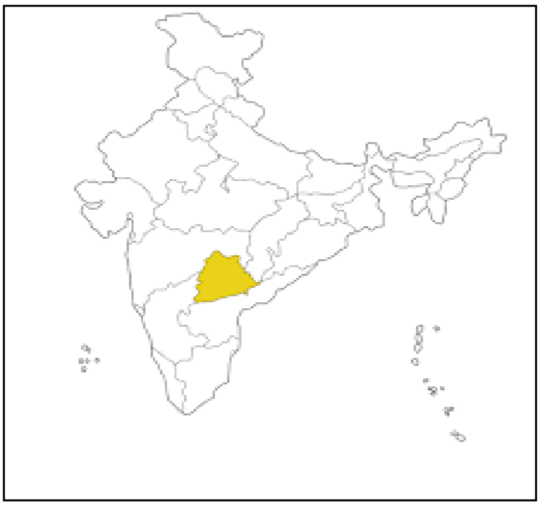

Fig. 1: Regions of Telangana Location

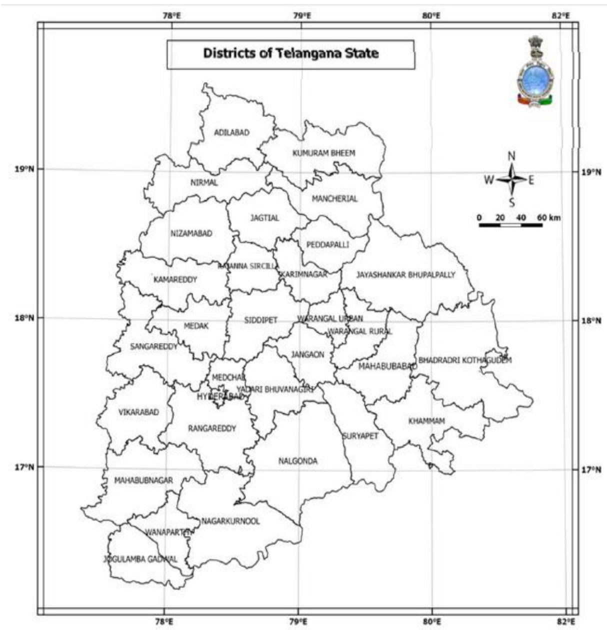

Fig. 2: state divisions

Table 2. The maximum rainfall in each SWM season

Month	Maximum downpour experienced in mm	Year
June	234.8	2000
July	492.6	2013
August	426.5	1990
September	248.7	2007
June-September	1133.1	2013
Annual	1384.7	2013

3. Methodology

Figure 3 illustrates the evaluation and comparison of SARIMA, GARCH, HWSM, and HLTM as part of the methodology used to forecast the amount of precipitation.

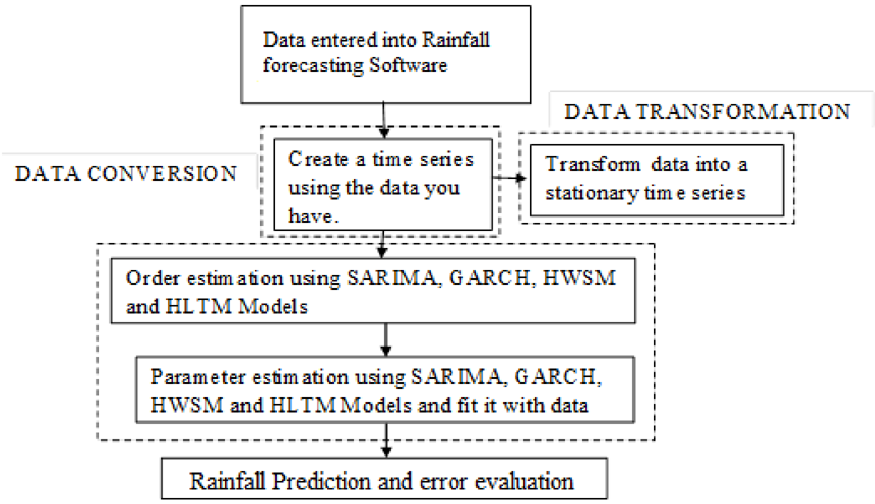

Fig. 3: Working Principle

3.1. Data Selection and Preprocessing

The two datasets utilized are DataSet-1 (DS-1), which comprises normalized data on atmospheric phenomena for each district and months from 1951 to 2000, and DataSet-2 (DS-2), which contains mean atmospheric phenomena data for each district from 1901 to 2015. These datasets have been compiled by IMD [12]. MAE, RMSE and MAE were utilized to evaluate the classification model's dependability.

3.2. SARIMA

The philosophy used to anticipate the precipitation include the Informational collection Determination, Information Preprocessing, and assessing and contrasting GARCH, SARIMA, HLTM and HWSM which are displayed in Fig.3.

3.3. GARCH

GARCH models are applied when the measure of variability of the error term is either constant or uniform. So, in a mathematical model based on statistical assumptions, heteroskedasticity refers to the uneven pattern of parameter variation. Data from time series are subjected to these analysis, which examines the contingent measure of variability. When applied to datasets having a positive excess kurtosis error and a large SD, it quantifies all multi-dimensional relationship. The model is a modified version of ARCH that additionally comprises of MA.

3.4. HWSM

Holt Winter's Exponential Smoothing and triple exponential smoothing are some names for it. This time-series forecasting methodology projects parameter estimates by accounting for both trend and seasonality.

In order to apply HWSM, periodic variables must first be exponentially smoothed. Level and trend are also included. Over a time overarching pattern of values is used frequently. In the sequence, the levels are the average values. Seasonality, commonly referred to as a repetition of a particular set of recordings taken with specific breaks. It consists of a evaluation formula and 3 smoothing formulae: Le_i, Tr_i, and Pe_i, which are expressed in eqn. (1), eqn. (2), eqn. (3) & eqn. (4) with 3 smoothing parameters α, β, and γ.

This formula shows the adjusted mean value of non-seasonal prediction and the season calibrated observation for period i. The trend formula is equivalent to HLTM. An identified mean value of the current time interval indicator and the previous season is shown by the below periodic formula.

Level Formula $$Le_i = \alpha(a_i - Pe_{i-l}) + (1-\alpha)(Le_{i-1} + Tr_{i-1}) \qquad \text{eqn. (1)}$$

Trend Formula $$Tr_i = \beta(Le_i - Le_{i-1}) + (1-\beta)Tr_{i-1} \qquad \text{eqn. (2)}$$

Seasonality/Periodicity Formula $$Pe_i = \gamma(a_i - Le_i) + (1-\gamma)Pe_{i-l} \qquad \text{eqn. (3)}$$

Prediction formula $$F_{i+n} = Le_i + \ n\,Tr_i + Pe_{i+n-l} \qquad \text{eqn. (4)}$$

Were *Le* represents Level, *F* indicates prediction at *n* duration, *a* represents observation, *Tr* is trend parameter, *Pe* specifies time interval indicator, $\alpha, \beta,$ and γ are constants that must be evaluated similar to MSE model as small as possible, *l* gives the duration of time interval patterns for *α, β and γ*, where *α, β* and *γ* resides between 0 and 1.

3.5. HLTM

Enhanced SES enables forecasting of data with a trend. The SES method known as HLTM is combined with the level and trend. Now this requires 3 formulas to be justified algebraically. The HLTM is composed of two smoothing equations, Le_i and Tr_i, which are represented by Equations (5), (6), and (7), respectively, and have smoothing parameters of and.α and β.

Level Formula $$Le_i = \alpha(a_i - Pe_{i-l}) + (1-\alpha)(Le_{i-1} + Tr_{i-1}) \quad (5)$$

Trend Formula $$Tr_i = \beta(Le_i - Le_{i-1}) + (1-\beta)Tr_{i-1} \quad (6)$$

Prediction formula $$F_{i+n} = Le_i + \ n\, Tr_i \quad (7)$$

4. Results and Discussion

We evaluated these approaches using their RMSE, MAE, and MSE values. Table 3 presents a comparison of the various Time-Series forecasting methods. Table 3 shows that HWSM had the lowest error rates for DS-1 and DS-2, respectively, 4.767 and 4.343 RMSE, 1.51 and 1.432 MAE, and 27.65 and 24.75 MSE. Fig. 4 and Fig. 5 shows the representation of MAE, MSE and RMSE values for the DS-1, DS-2 for each of the models of time series forecasting that were taken into consideration.

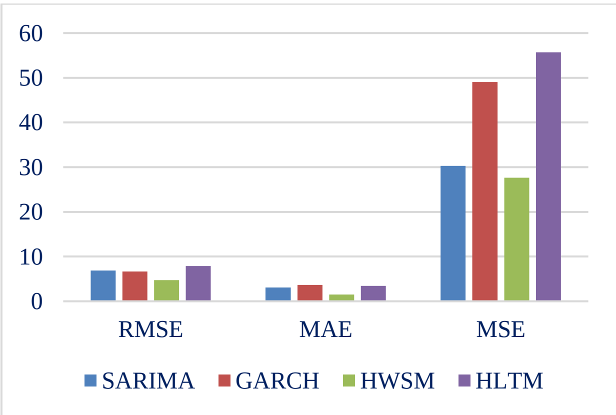

Fig. 4: Forecasting models of MAE, MSE and RMSE values of Dataset - 1

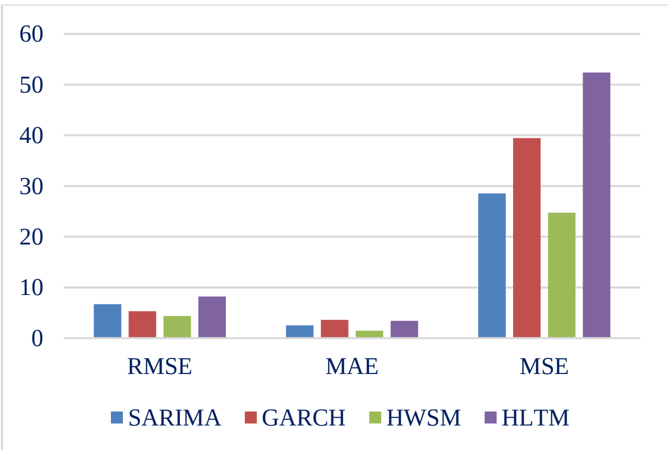

Fig. 5: Forecasting models of MAE, MSE and RMSE values of Dataset - 2

Table 3. Comparison Forecasting Models in time intervals.

Model	RMSE		MAE		MSE	
	DS-1	DS-2	DS-1	DS-2	DS-1	DS-2
SARIMA	6.856	6.706	3.1	2.541	30.260	28.542
GARCH	6.682	5.280	3.678	3.59	49.021	39.443
HWSM	**4.767**	**4.343**	**1.51**	**1.432**	**27.65**	**24.75**
HLTM	7.912	8.241	3.462	3.394	55.723	52.390

5. Conclusion

This research offered a Comparative Forecasting Models in time intervals for evaluating rainfall in Telangana state. The results show that HWSM outperforms the alternative strategies in terms of RMSE, MSE and MAE. The HLTM, HWSM, SARIMA, and GARCH time-series forecasting models were evaluated. It is clear that HWSM has the lowest error rates for datasets 1 and 2, with 4.767 and 4.343 RMSE, 1.51 and 4.432 MAE, and 27.65 and 24.75 MSE, respectively.

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